ELSEVIER
Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia Engineering 16 (2011) 348 – 355
Procedia Engineering
www.elsevier.com/locate/procedia

International Workshop on Automobile, Power and Energy Engineering

Study on the application of Genetic Algorithms in the optimization of wireless network

WANG Yan[a], SHAN Xin-xin[a], SUN Yan-ming[b],a*

[a]College of Electrical and Control Engineering ,Liaoning Technical University,Liaoning Huludao 125105,China
[b] Sany Heavy Industry CO.,LTD,Liaoning Shenyang 110027,China

Abstract

Wireless sensor network can eliminate the high cost of wired network. However, in wireless sensor networks, an important but critical problem is the energy consumption of sensor nodes greatly limits the working life. The paper combining the application of genetic algorithm for wireless sensor networks in multi-objective optimization, taking into account the needs of specific application, a sensor network in the open pit slope detection example is introduced. Fitness function is designed according to the application of open-pit mine slope detection system. In the same conditions, using serial genetic algorithm, parallel genetic algorithm and quantum genetic algorithm for network energy optimization. Simulation results show that: genetic algorithm optimize the energy consumption, achieve the longest life cycle of the network. By comparing these three kinds of genetic algorithms, the quantum genetic algorithm is much better than the other two genetic algorithms in optimizing the energy consumption.

Keywords: Wireless Sensor Networks; Genetic Algorithms; Fitness function；Energy optimization

1. **Introduction**

Wireless sensor network (WSN) has been concerned in many field for its low power consumption, easy maintenance, easy distribution networks and many other advantages[1]. Compared with wired

* Corresponding author. Tel.: 15041832816
E-mail address: fortunate_w@163.com
Coal Association Program 2011（No. MTKJ2010-294）

doi:10.1016/j.proeng.2011.08.1094

networks, WSN greatly is limited by energy. It is very difficult for wireless network nodes to replace the batteries, even impossible. The optimization of the network is to optimizing the network energy consumption and prolonging the working life of the whole network.

Fitness function is designed according to the application of open-pit mine slope detection system. Serial genetic algorithm (SGA), parallel genetic algorithm (PGA) and quantum genetic algorithm (QGA) is used to optimize the energy of WSN, including the working conditions of sensor nodes, the selection of cluster-head and the signal transmission distance of working nodes. By using three genetic algorithm in network optimization, the effectiveness of using genetic algorithm in the system is proved by the simulation results, the using of the genetic algorithms are also compared in this system.

2. Wireless Sensor Network Model Construction

The applications and design methods of WSN are already used commonly, but taking into account the specific application environment for the open pit slope detection, a specific framework are proposed to validate the performance of genetic algorithm[2].

2.1 Network Model

The characteristic of the open pit slope detection network model is as follows: The network is constituted by the length of 10 × 10 square grid, and the sensor nodes are placed in the 100 points of grid intersection. The communication protocol is single-hop cluster structure to ensure the connectivity[3][4]. Using cluster structure, the sensor nodes in monitoring area have four operating modes: cluster-head mode(CH), high-power transmission mode (HS), low power transmission mode (LS) and dormant mode (DOM), supposing the energy consumption ratio of CH, HS, LS DOM as 20:2:1:0.

2.2 The Fitness Function

To prevent the energy consumption is not averaged in WSN and because of the energy exhausted prematurely some nodes disrupt the whole net, genetic algorithms is used to optimize the energy of each node to ensure energy consumption averaged[5]. In this paper,the fitness function is consisted of three sets of important parameters based on the open pit slope detection network , that is, the multi-objective function is mixed into a single objective function. The objective fitness function is as follow:

$$f(x)= 1/(a_1 \times DSE + a_2 \times SCE + a_3 \times SORE + a_4 \times FC + a_5 \times OE + a_6 \times CE + a_7 \times BCP) \qquad (1)$$

The parameters of DSE (Dormancy Sensors Error), SCE (A Sensors-per-CH Error), SORE (A Sensors-Out-of-Range Error), FC (Field Coverage Rate), OE (Operational Energy), CE (Communication Energy), BCP (Battery Capacity Penalty) according to [3][6]. Fitness function is a weighting function. The significance of each parameter is defined by setting appropriate weighting coefficients. According to our simulation, the selected values are shown in table 1.

Table 1. Weight coefficient

a_1	a_2	a_3	a_4	a_5	a_6	a_7
900	100	100	9000	-50	0.2	1

According to the shortcoming that linear fitness function is constant in the evolution of SGA, Goldberg linear stretch is used to improve the fitness function with expand the differences between individuals. So, the fitness function of this design is as follows:

$$f^{*}(x)=\frac{(c-1)f_{avg}}{f_{\max}-f_{avg}}f(x)+\frac{f_{\max}-cf_{avg}}{f_{\max}-f_{avg}}f_{avg} \qquad (2)$$

In the above, c is the number of best individual expectations. In this experiment, c =2.

3. Genetic algorithm for the optimization of wireless sensor network

3.1 Serial genetic algorithm experiment

In sensor nodes, the cluster-head nodes collecte information from ordinary node and transmit the information to the base station, it will consume most energy, so the number of cluster-head nodes must be limited. High-power transmitter nodes transmit information farther than low-power transmitter nodes, consume more energy. In order to save energy consumption, the number of high-power transmitter nodes must be reduced, and the number of low-power transmitter nodes should increased and some nodes work in dormant mode in different cycles.

Based on binary code, network nodes run in four modes: dormant node (00), low-power transmitter node (01), high-power transmission node (10), cluster-head node (11).

The control parameters of genetic algorithm including chromosome string length, population size, the crossover rate and mutation rate. In these examinations, the number of nodes in the network is 100, each node express with 2-bit binary code, so chromosome string length is 200. The optimal population size in the project is 80 to get the maximum fitness value. A large number of experiments have been done between crossover probability from 0.4 to 0.9 and mutation probability from 0.001 to 0.1, and the results show that when the crossover probability is 0.8 and mutation probability is 0.005, the fitness value is the maximum. The simulation results are shown in Fig. 1.

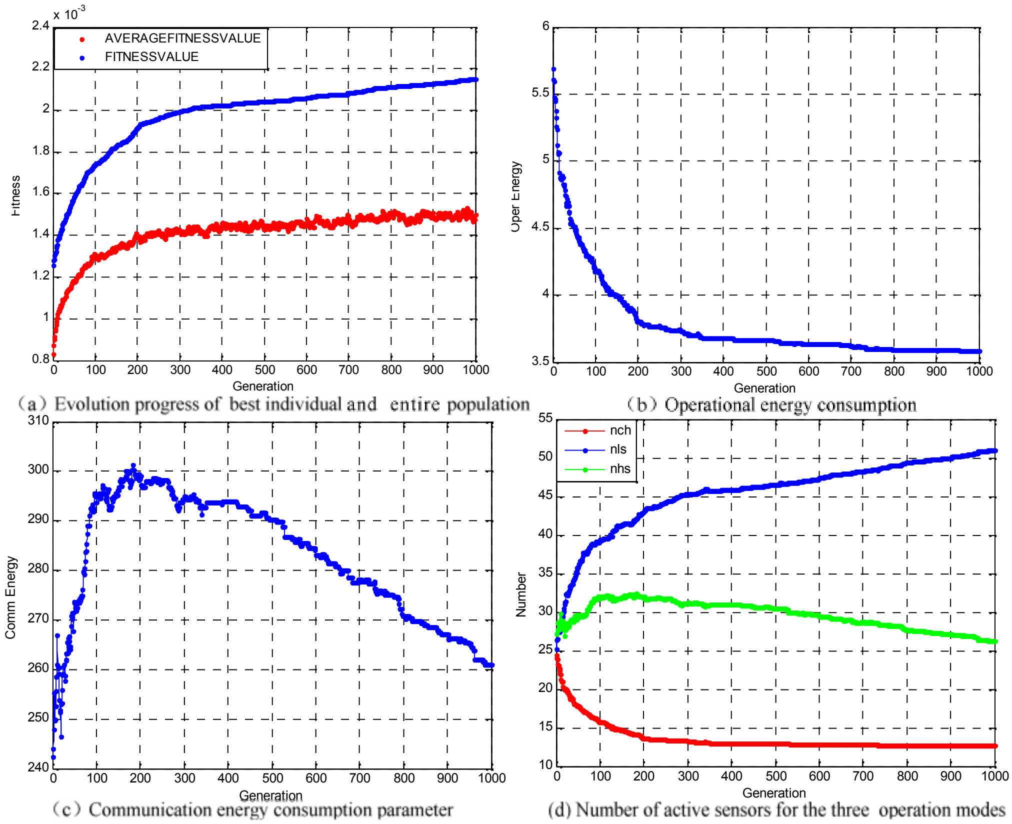


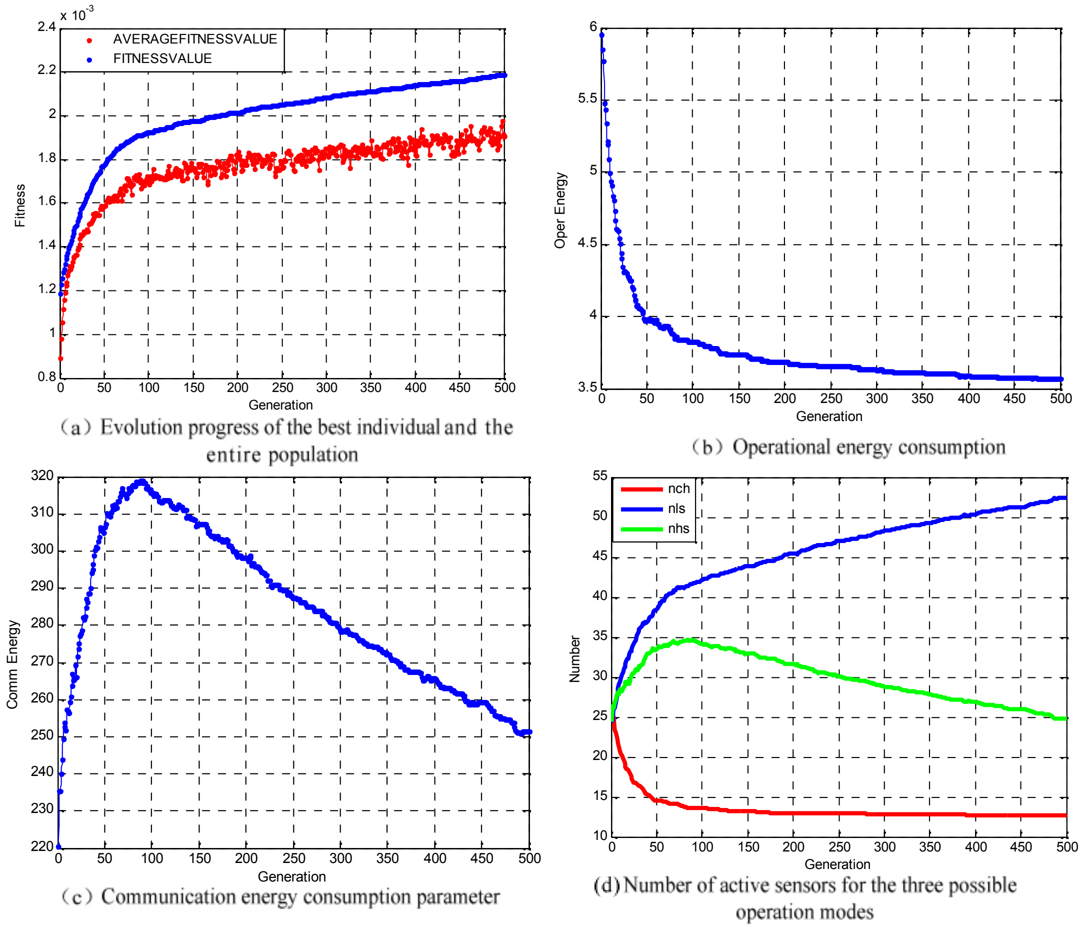
Fig. 1 The SGA evolution of average process of 15-cycle network

Fig. 1(a) shows the best individual and the average value of fitness function among 15 cycles. From the growth of average fitness of population, it can be seen that genetic algorithm can optimize the population. Fig. 1(b) shows the evolution process of the system energy consumption. The curves decrease rapidly and then become steady in the end. Fig. 1(c) shows the energy consumed in communication. It reached a peak in the 180-generation, then decline steadily. Compared with CH, HSR and LSR consume less energy. However, considering the larger number of HSR and LSR, this energy consume must be limited. Fig. 1(d) shows the statistical number of nodes working in different modes.

From the above analysis we can see the energy optimization of SGA: the great majority of network nodes work in power-saving mode, which can ensure that the network working life is extended.

3.2 Parallel Genetic Algorithm Experiment

For some large projects, many of individuals in population need lots of computation by SGA. A large number of population individuals calculate the fitness will make the evolution process slowly. It is difficult to achieve the required of calculation speed, so through the practice based on the network model, here we used PGA to meet the design requirements. The simulation results are shown in Fig.2



（a）Evolution progress of the best individual and the entire population

（b）Operational energy consumption

（c）Communication energy consumption parameter

(d) Number of active sensors for the three possible operation modes

Fig. 2 the PGA evolution of average process of 15-cycle network parameters

The population group is divided into several sub-populations. Each sub population with their evolution processing algorithm is set to different computers. So, the genetic evolution process of each group can be calculated independently on different computers.

The population group is not independent of each other, so they need to exchange some information. The model for exchange the information is called coarse-grained PGA. The application premise of the model is that sub-populations on each computer must be included more than one individuals and each sub population in different computers run SGA independently. After a cycle of computing, select two computers randomly to exchange the populations information. The coding mechanism is the same as SGA, and 4 computers are choosed in our simulation. After each cycle their best individuals information are exchanged. At last, we select one group randomly to describe PGA, though the other three groups is differently, the final result are similar.

To illustrate the superiority of PGA, the choice of operating parameters are the same as SGA, and the fitness function weight are not changed. Through the comparison of Fig. 1 and Fig. 2, we can see the same trend of the two figures and eventually reaching the purpose of optimizing the WSN. However, PGA only run 500 generations already achieve the effect that SGA run 1000 generations.

Thereby, though Fig. 2 proved that the PGA optimize network is faster than SGA. Picture in Fig. 2 express the same meaning as Fig. 1, here we are not repeated.

3.3 Quantum genetic algorithm Experiment

The design using single-quantum bit encoding, with a pair of complex number to define a quantum bit. Thus, a chromosome can use the single-quantum of following form to encoded[7].

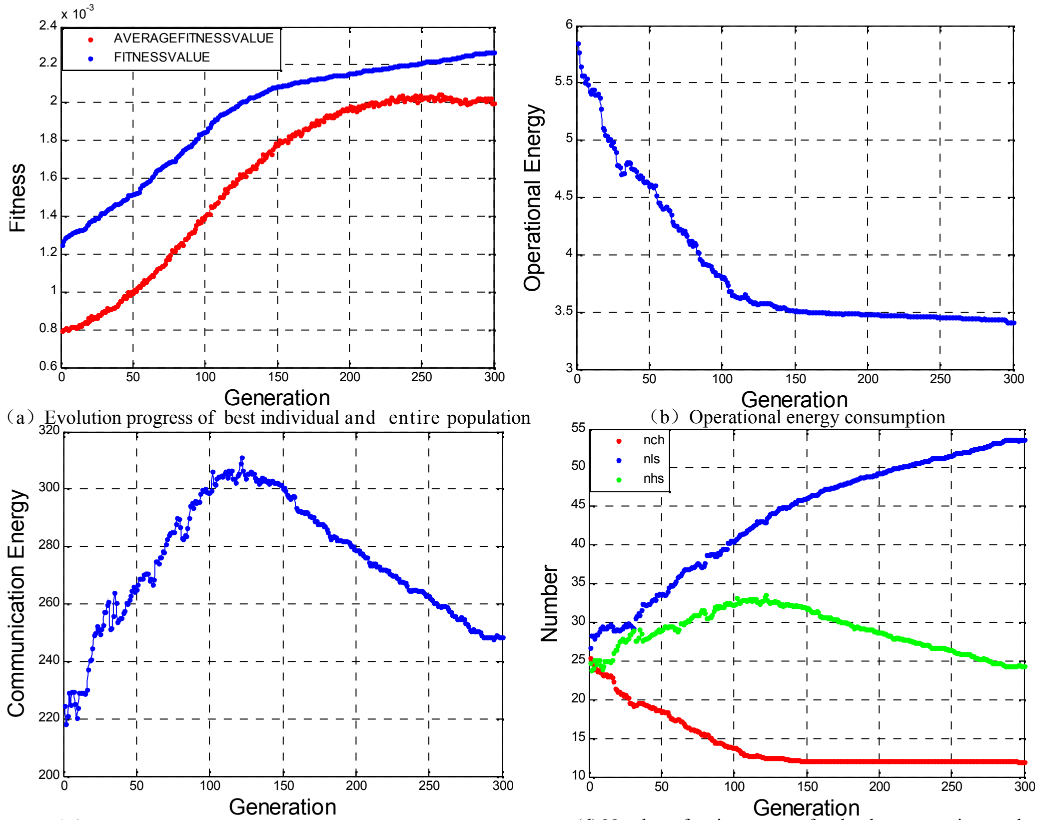
$$Q = (q_1, q_2 ......q_k) = \begin{pmatrix} \alpha_1 & \alpha_2 ......\alpha_k \\ \beta_1 & \beta_2 ......\beta_k \end{pmatrix} \tag{3}$$

k in the formula is the number of chromosome genes, each gene consists of a quantum bit ($q_k = [\alpha_k \ \beta_k]^T$). α and β are the probability amplitude of |0> and |1>. Each quantum bit is the superposition of qubit, not a defined state. From a single chromosome Q, it is impossible to get a certain coding. Therefore, each gene (probability amplitude) in qubit encoding needs a measurement to get a certain coding (|0> or |1>). Sensor nodes may run in four modes, coded as follows: sleep node (|0> |0>), low-power transmitter node (|0> |1>), high-power transmission node (|1> |0>), cluster head node (|1> |1>).

In quantum theory, the transfer between various states is achieved by transform matrix of quantum gate. QGA in the state transition process join the information of optimal individual to generate the rotating gate and accelerate the algorithm convergence. We design the following quantum rotating operator to accelerate the evolution.

$$\text{WhirlGate}(\theta_i) = \begin{pmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{pmatrix} \tag{4}$$

In the above, $\theta_i = \Delta\theta \times f(\alpha_i, \beta_i)$. $f(\alpha_i \ \beta_i)$ and $\Delta\theta$ represent the rotation direction and angle, the choice of $\Delta\theta$ must be reasonable, if $\Delta\theta$ is too large, algorithm is easy to converge to local optimum and lead to the premature phenomenon. On the contrary, if $\Delta\theta$ is too small, the search speed is too slow even at a standstill. The traditional quantum algorithm in the choice of $\Delta\theta$ has a fixed value between 0.001π to 0.1π. After repeated experiments, discovered that $\Delta\theta$ will be better as a variable to accelerate global optimization. $\Delta\theta$ =0.035π×step, step is variable step size. On the premise of $\Delta\theta \in [0.001\pi \ 0.1\pi]$, choose 1 and the largest algebra as starting point and ending point, and then select a reasonable point between starting point and ending point. Through the three points, we will get a function by cubic spline interpolation, and then calculate the function value as the rotating angle of each generation corresponding to the algebra angle of each generation. The entire optimization process is adjusted effectively by the changing of Δθ.



（a）Evolution progress of best individual and entire population

（b）Operational energy consumption

（c）Communication energy consumption parameter

(d) Number of active sensors for the three operation modes

Fig. 3 the QGA evolution of average process of 15-cycle network parameters

Table 2 Comparison of network design parameters

	GA1	GA2	GA3
Generation	1000	500	300
DSE	0	0.1	0
FC	0.8	0.8	0.8
OE	3.78	3.85	3.55
CE	230	323	203
Active	90	89	90
CH	14	14	13
HSR	22	29	18
LSR	54	47	59
CH/ Active	0.156	0.146	0.144
HSR/ Active	0.244	0.322	0.2
LSR/ Active	0.6	0.522	0.66
Fitness	0.002136	0.002017	0.002326

To illustrate the QGA is better than SGA and PGA, the operating parameters are the same as SGA and PGA, and the weight of the fitness function value is unchanged. Comparing Fig. 1, Fig. 2 and Fig. 3, we can see the same trend of the two figures and eventually reaching the purpose of optimizing the WSN. But the QGA only run 500 generations already achieve the effect that SGA run 1000 generations and PGA run 500 generations, what is more, QGA calculate on a single computer. Therefore it can prove that QGA has a faster optimization effect than SGA and PGA.

Table 2 lists the single-cycle data for the QGA and the traditional genetic algorithm. As can be seen in table 2, the advantage of QGA is obviously. (GA1 is serial genetic algorithm, GA2 is parallel genetic algorithm, GA3 is quantum genetic algorithm). By Table 2, we can see the searching efficiency of QGA is much better than SGA and PGA. It will save a lot of time and only need one computer to calculate.

4. Conclusion

Taking into account of the energy limitations in WSN, genetic algorithm are used to optimize the WSN. The background of this paper is open pit slope detection, as the features of the application requirements, communication constraints, energy saving and so on. This paper presents the design of energy optimization by optimizing the network nodes operating mode[8].The main work are as follows:

(1). In this paper, a kind of network architecture is established based on cluster structure. The network nodes communicate with the nearest cluster-head node.

(2). The genetic algorithm optimize the open pit slope detection system with determine the status of nodes in the network and select the cluster head in WSN.

(3). According to our model structure, we defined the most important parameters: dormant parameters, connectivity parameters and energy parameters to form the fitness function.

(4). SGA, PGA and QGA is used to optimize the energy of WSN. A reasonable network model and the working status of each node are received. By the same model and parameters, compared with the average evolutionary process in three genetic algorithms, the results show that: the QGA is better than the other two genetic algorithms.

Simulation results demonstrate the superiority of genetic algorithm: genetic algorithms in WSN can optimize the network energy. Through the application of QGA in WSN, not only optimize the network energy consumption, but also achieve the longest life cycle of the network.

5. References

[1] Yong M, Yu Y, Yan W, Ling L. *Optimization design of coal mine wireless body sensor network based on Genetic Algorithm*, the Proceedings of IEEE-NSWCTC2009, Wuhan China, June 2009

[2] Houtian Hu, *Slope geological hazards prediction*,Southwest Jiaotong University Press, 2001.3, china.

[3] Wang Yan, Sun Yan-ming, Yu Bao-qing, Ma Yong, *The optimization of wireless sensor networks in the open-pit mine slope detection base on quantum genetic algorithms*, The 1st International Conference on Electrical and Control Engineering, Wuhan China, June 25-27, 2010, Wuhan, China

[4] Wang Yan, Zheng Ya-ru, Ma Yong，*Study on the Coal Mine Personnel Position System Based on Wireless Body Sensor Networks*，the Proceeding of IEEE-Body Sensor Networks, Hong Kong, 2008,06

[5] Zhou Ming, Sun Shu-dong. *Genetic algorithms: theory and applications*, National defense industry Press, 1999, china.

[6] Konstantinos P. Ferentinos, Theodore A. Tsiligiridis, *Adaptive design optimization of wireless sensor networks using genetic algorithms*, Computer Networks 51 (2007) 1031–1051

[7] Michael A.Nielsen, Isaac L. Chuang, *Quantum Computation and Quantum Information* . Cambridge University Press 2000.

[8] Amol P. Bhondekar*, Member, IAENG, Renu Vig, Madan Lal Singla, C Ghanshyam, Pawan Kapur, *Genetic Algorithm Based Node Placement Methodology For Wireless Sensor Networks*, Proceedings of the International MultiConference of Engineers and Computer Scientists 2009 Vol I IMECS 2009, March 18–20, 2009, Hong Kong